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Dynamic Hand Gesture Classification Based on Radar Micro-Doppler Signatures

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Abstract: Dynamic hand gesture recognition is of great importance for human-computer interaction. In this paper, we present a method to discriminate the four kinds of dynamic hand gestures, snapping fingers, flipping fingers, hand rotation and calling, using a radar micro-Doppler sensor. Two micro-Doppler features are extracted from the time-frequency spectrum and the support vector machine is used to classify these four kinds of gestures. The experimental results on measured data demonstrate that the proposed method can produce a classification accuracy higher than 88.56%.

Keywords: hand gesture classification; micro-Doppler signatures; support vector machine; human-computer interaction

I. INTRODUCTION

Hand gesture, as an important style of interpersonal communication, is regarded to be an ideal method of human-computer interaction (HCI). With the development of computer, there has been a significant amount of research in hand gesture recognition. The video based methods presented in [1-3] can recognize 2-D, 3-D, or real-time hand gestures. However, their performances depend on the environment conditions such as light, dust, rain, etc. Moreover, a high resolution camera is required to catch fast gestures, which may significantly increase the hardware cost.

Radar micro-Doppler effect is known as a phenomenon caused by the micro-motion of an object or its parts. There has been a number of research on human movement analysis by using micro-Doppler features [4],[5]. Along with the torso movement, different motions of arms, legs and other parts of the body result in different micro-Doppler components [4]-[9]. Therefore, micro-Doppler signatures can be used to classify the human activities, such as crawling, walking, and running, and to recognize the unarmed/armed person, even to distinguish human from animals [6]-[8]. Compared to video-based methods, the radar micro-Doppler analysis is all-weather and unaffected by natural light conditions and, therefore, is worth investigating for robust HCI systems. There has been some literature on dynamic hand gesture using radar sensors[11]-[12]. Features are extracted from the Doppler shift images, then a K-Nearest Neighbor (KNN) classification approach is used to classify four gestures in [11]. In [12], the authors extract features from the range-Doppler map.

In this paper we focus on classification of four kinds of hand gestures including snapping fingers, flipping fingers, hand rotation and calling, by extracting the micro-Doppler signatures from the time-frequency domain and utilizing a support vector machine(SVM). SVM has been combined with micro-Doppler analysis in [6] for recognition of different kinds of human motions. The difference between the proposed method and that in [6] lies in the distinction of the feature selection. The experimental results on measured data demonstrate that the proposed method can produce a classification accuracy higher than 88.56%.

The paper is organized as follows. Section II introduces the experimental setup to collect data with a continuous wave (CW) radar. Section III describes the proposed method, including time frequency analysis, feature extraction and classification. Section IV provides the classification results using SVM. The conclusions and remarks are given in section V.

II. EXPERIMENT SETUP AND DATA COLLECTION

Measured data of 4 kinds of dynamic hand gestures are collected using a CW radar system. The carrier frequency of the radar is 9.8GHz. The experiment is performed in an indoor environment. Only one man participates in the experiment to obtain hand gestures data. And the body of the tester, especially the arm should remain static during the experiment. The distance between the hand and the radar is approximately 30cm.

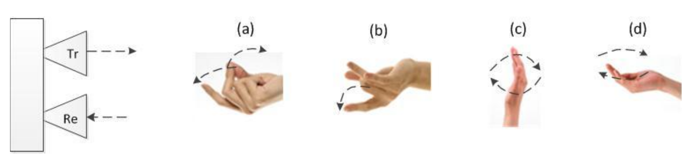

Fig.1. Illustrations of four kinds of hand gestures. (a) snapping fingers. (b) flipping fingers. (c) hand rotation. (d) calling

The hand gestures to be recognized include (a) snapping fingers, (b) flipping fingers, (c) hand rotation, (d) calling. An illustration of these gestures is shown in Fig. 1. And the

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descriptions of the gestures are given in Table. I. Each gesture is measured 50 time, 4s for each time.

TABLE I. DYNAMIC HAND GESTURES DESCRIPTION

Hand gesture	Description
(a)snapping fingers	The act of pressing the middle finger and the thumb together and flinging the middle finger onto the palm while the thumb sliming forward quickly
(b) flipping fingers	The act of buckling the middle finger under the thumb and then flipping the middle finger forward quickly
(c) hand rotation	The act of rotating the hand clockwise/unclockwise and keeping the wrist rest
(d) calling	The act of calling someone with the fingers swinging back and forth together

III. THE PROPOSED METHOD

The proposed method will be described in this section.

A. Time-frequency analysis

The time-frequency distributions of these four gestures obtained by short-time Fourier transform (STFT) are shown in Fig. 2. The strongest component in each time-frequency distributions in Fig. 2, corresponding to the static torso, is around 0Hz. In what follows, we will describe the relationship between the spectrograms and the micro-motions. From Fig. 2 (a) we can see that the gesture of snapping fingers has two discontinuous motions in each period. The red arrow in Fig.2(a) indicates a high negative frequency peak and a smaller positive frequency peak, which corresponds to flinging the middle finger onto the palm and flinging the thumb forward quickly. The second motion of snapping fingers is going back to initial status, as indicated by the yellow arrow in the Fig. 2(a). From Fig. 2(b) we can see that the gesture of flipping fingers has two discontinuous motions in one period too. The red and yellow arrows represent the two motions, respectively: flipping the middle finger forward quickly and the motion of recovery. In Fig. 2(c), we can find that the gesture of hand rotation is a continuous motion. As the red arrow indicates, the micro-Doppler frequency changes along with the time, like a sine wave. From Fig. 2(d), we can see that the gesture of calling has two motions. The red and yellow arrows represent the motions of waving swing the fingers back and forth, respectively. The components labeled by green arrows in Fig. 2(b), (c), (d) are caused by the I/Q imbalance of the radar.

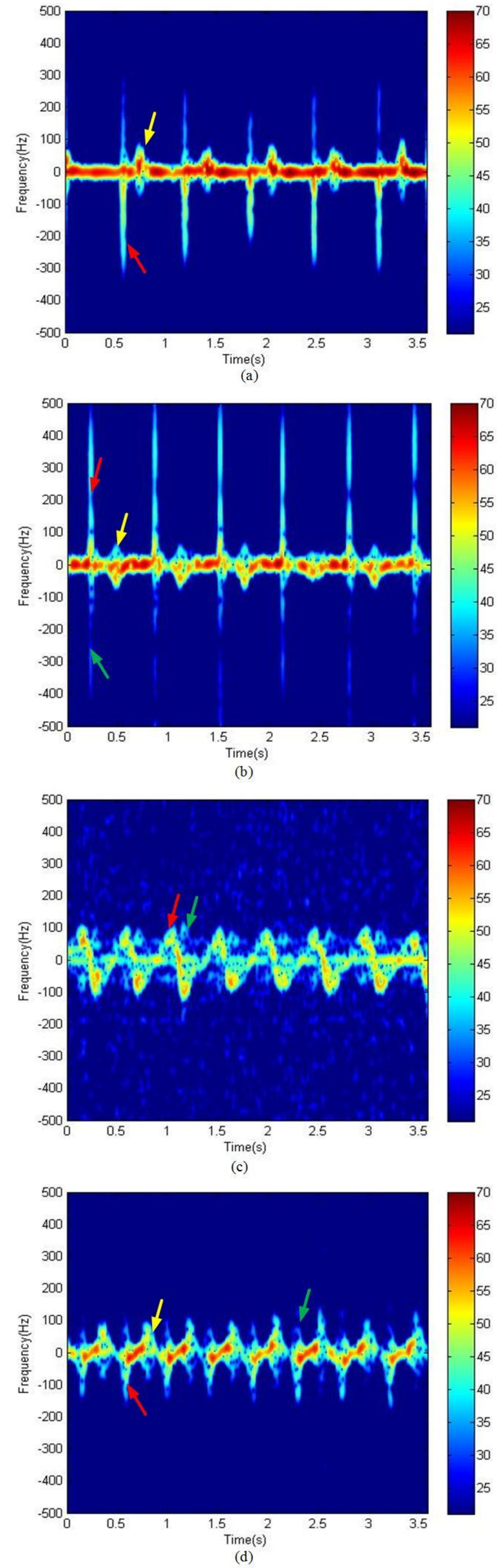

Fig.2. Time-frequency distributions of the four measured hand gestures. (a) snapping fingers. (b) flipping fingers. (c) hand rotation. (d) calling

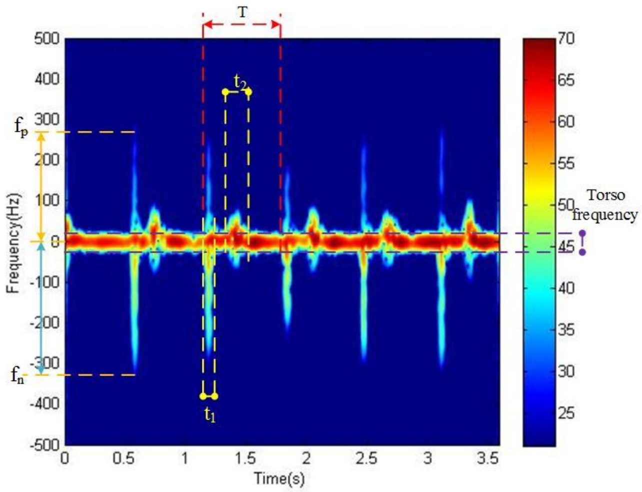

Fig.3. Selected features of the micro-Doppler spectrogram

B. *Feature extraction*

Two features are selected to describe the gestures: the ratio of negative-positive frequency and the duty cycle.

According to the spectrograms, the four gestures have distinct micro-Doppler characteristics from each other. In Fig.3, taking the gesture of snapping fingers as an example, we discuss about the features extraction. Denote the static torso as *Torso frequency*, the period of the whole gesture as T, the duration of motion one and motion two as t_1 and t_2, respectively, the positive frequency value and the negative frequency value as f_p and f_n, respectively. Then we could define the two features as follows:

(1) Ratio of negative-positive frequency R_a. This is the ratio of the negative and positive frequency peaks of each gesture:

$$Ra = \frac{|f_n|}{|f_p|}, \tag{1}$$

where $|f_n|$ is the absolute value of the negative frequency peak, and $|f_p|$ is the absolute value of the positive frequency peak.

(2) Duty cycle D. This is the percentage of one period in which the signal of the gesture is active:

$$D = \frac{\sum_{n=i}^{N} t_i}{T} \times 100\%, \tag{2}$$

in which D is the duty cycle, $\sum_{n=i}^{N} t_i$ is the duration of all the motions in the gesture, N is the number of the motions, t_i is the duration of the i-th motion, and T is the period of the gesture.

From Table. II it can be seen that the selected features are capable of distinguishing the four kinds of gestures of interest. The typical ranges of the features of the four gestures are listed in Table II.

TABLE II. RULES OF THE FEATURES

Hand gesture	Features	
	(1) ratio of negative-positive frequency	***(2) duty cycle***
(a) snapping fingers	large	small
(b) flipping fingers	small	small
(c) hand rotation	moderate	large
(d) calling	large	moderate

C. *Classification*

The last step of the proposed algorithm is to perform classification based on the features we extract in the previous step. Here SVM is used as the classifier. Base on learning the support vectors from the training data set, SVM can make a binary classification with high accuracy.

In this paper, four dynamic hand gestures need to be classified. In order to solve the multiclass problem, we apply three SVMs to form a decision tree classifier as shown in Fig.4.

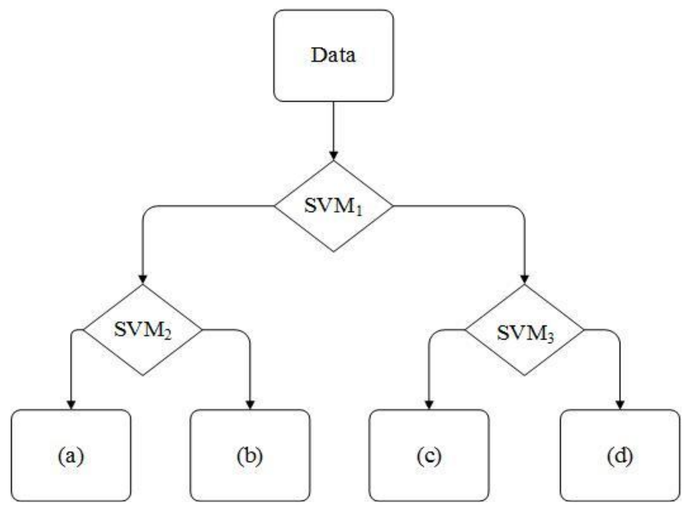

Fig.4. The t decision tree classifier. (a) snapping fingers. (b) flipping fingers. (c) hand rotation. (d) calling

SVM_1 separates the four gestures into two groups: the gestures of snapping and flipping fingers as the first group, the gestures of hand rotation and calling as the second group. Then, in the first group, SVM_2 distinguishes the snapping fingers and the flipping fingers, and in the second group, SVM_3 distinguishes hand rotation and calling.

IV. CLASSIFICATION RESULTS

The feature samples distribution of the experimental data is shown in Fig.5. We collected 50 data recordings for each gesture. The two axes denote the two values of samples for the two features, i.e., the ratio of negative-positive frequency and the duty cycle, respectively. In Fig. 5, the feature vectors of the four gestures are almost clustered in different regions, which allows us to classify them via three SVMs.

To verify the performance of the proposed algorithm, we randomly divide the entire data into 5 groups , where 4 groups are used as the training data and the rest group of data are used for test. The accuracy rates are shown in Table III.

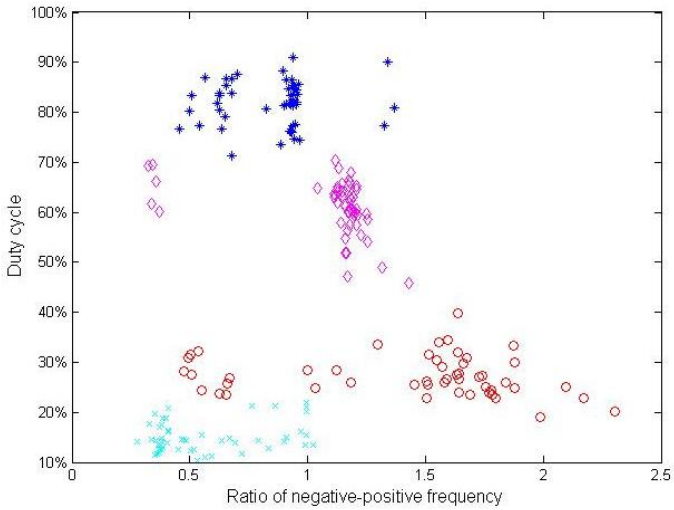

Fig.5. Feature distributions of the experiment data

TABLE III. CONFUSION MATRIX OF THE FOUR GESTURES

Decision	Truth			
	(a)	(b)	(c)	(d)
(a)	98.49%	5.12%	0	0
(b)	1.51%	94.88%	0	0
(c)	0	0	92.58%	11.44%
(d)	0	0	7.42%	88.56%

As shown in Table III, the proposed method can distinguish these four gestures with the success rate higher than 88.56%. In addition, we also can see from Fig. 6 that SVM_1 perfectly distinguish the four gestures into two groups with no error..

V. CONCLUSION

In this paper, we demonstrated the effectiveness of the micro-Doppler signatures for classification of four kinds of hand gestures that may be used in HCI applications. Two micro-Doppler features, i.e., the ratio of negative-positive frequency and the duty cycle were extracted from the time-frequency domain. A decision tree classifier based on three SVMs can provide the classification accuracy higher than 88.56%. It is worth emphasizing that the feature selection is closely related to the gestures required for HCI systems. That is to say, if one is interested in other gesture styles, the feature selection may vary accordingly.

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